International Journal of Computer Science Engineering
and Information Technology Research (IJCSEITR)
ISSN(P): 2249-6831; ISSN(E): 2249-7943
Vol. 5, Issue 1, Feb 2015, 43-54
TJPRC Pvt. Ltd.

ASSESSMENT OF ANS USING HRV DATA IN DISEASED CONDITION

D MAHESH KUMAR[1], PRASANNA KUMAR S. C[2], B. G SUDARSHAN[3], YADHURAJ S. R[4] & HEMANTH KUMAR[5]

[1,5]Assistant Professor, Department of Electronics and Instrumentation Engineering JSSATE, Bangalore, Karnataka, India

[1]Ph.D Scholar, Jain University, Bangalore, Karnataka, India

[2]Professor & HOD, Department of Electronics and Instrumentation Engineering, RVCE, Bangalore, Karnataka, India

[3]Associate Professor, Department of Electronics and Instrumentation Engineering, RVCE, Bangalore, Karnataka, India

[4]Ph.D Scholar, Department of Electronics and Instrumentation Engineering, RVCE, Bangalore, Karnataka, India

ABSTRACT

Heart Rate Variability (HRV) is defined as the variation in the interval between consecutive heart beats. HRV is a powerful non-invasive tool to diagnose the cardiac diseases and also predicts the impending cardiac diseases. The present work is concentrated on such assessment of ANS using real time data acquired using Lab VIEW and processed using MATLAB. This work is to bring out the status of ANS of particular diseased patients by using HRV data by employing different analyzing techniques. Methodology: The methodology of project is to takeout the ECG data of various subjects having different health condition like healthy, diabetic, pre-diabetic, and hypertensive parameters using Lab VIEW ECG acquisition system and Lab VIEW signal express tool for real time data acquisition, and also data can be download from standard sites like Physionet, MIT-BIH database etc., then signal is manipulated with some pre-processing techniques to extract R-R interval (Inter Beat Interval) data. In next step, HRV feature extraction code yields heart rate variability features by taking text IBI input, both IBI and HRV feature extraction are done using MATLAB R2011a tool by developing an appropriate code for it. The obtained parameters are fed into Alyuda NeuroIntelligence neural network tool to classify data by analyzing it with a suitable network structure to find out condition of patient. The collected real time ECG data are analyzed quantatively and classified as healthy, diabetic, pre-diabetic or hypertensive data. Lab VIEW data is used for real time data acquisition and MATLAB tool is used for feature extraction and neural networks are used for data classification having user friendly feature with more accurate results. This study yields valuable results in the field of HRV to analyze, and for efficient classification of data of different diseased and healthy subjects. The work reveals that there is prominent decrease in HRV due diabetes and ageing; hence results in parasympathetic neuropathy. As tested in our laboratory conditions the obtained results are having nearly 99% accuracy.

KEYWORDS: HRV, Lab View Tool, MATLAB, Neuorintelligence Network, Sympatho-Vagal Balance, Autonomic Nervous System

INTRODUCTION

Human body is controlled by the action of Nervous System. The whole Nervous System (NS) is divided in to Somatic Nervous System (SNS) and Autonomous Nervous System (ANS). SNS controls the voluntary muscles (Locomotors organs) of the body while ANS controls in-voluntary muscles (Visceral organs) of body. An abnormality of the body alters the action of ANS, which is indicated by deviation of physical parameter from normal values, one of such is

Heart Rate Variability (HRV). HRV is defined as the variation in the interval between consecutive heart beats. Heart rate variability is generally measured using the electrocardiogram to generate an electrocardiograph. The electrocardiogram records electrical impulses sent out by the heart each time it beats. HRV can be visualized in Electrocardiogram clearly.

Autonomous Nervous System (ANS)

It is a part of central nervous system, which controls movement of involuntary muscles. ANS is divided into two parts, Sympathetic nervous system and Para sympathetic nervous system [2].

Heart Rate Variability

Heart rate variability (HRV) is the study of the various component rhythms and influences contributing to the overall phenomenon of heart rate [1]. Heart rate variability is a non-invasive electrocardiographic marker reflecting the activity of the sympathetic and parasympathetic components of the ANS on the sinus node of the heart.

Clinical Significance of the HRV

The analysis of HRV signal places a significant role in the assessment of cardiac health status. HRV decreases in many clinical condition such as cardio vascular dysfunction (hyper tension), diabetes mellitus, coronary artery disease, screening the patient with obstructive sleep apnea. Linear and non-linear analysis of HRV is also used for studying the different stages of sleep, sleep disorder and heart failures [7].

Aim of Study

The aim of the project is to quantify the ECG data into the HRV data by finding the R-R intervals. Feature extraction of HRV is done using generated R-R data to have conclusion on subject's state of nervous system with the help of neural network tool.

The methodology of project is to takeout the ECG data of various subjects having different health condition like healthy, diabetic, pre-diabetic, and hypertensive parameters using LabVIEW ECG acquisition system and LabVIEW signal express tool for real time data acquisition, and also data can be download from standard sites like Physionet, MIT-BIH database etc., then signal is manipulated with some pre-processing techniques to extract R-R interval (Inter Beat Interval) data. In next step, HRV feature extraction code yields heart rate variability features by taking text IBI input. The obtained parameters are fed into a neural network tool to classify data by analyzing it with a suitable neural network structure to detect the status of subject

MATERIALS AND METHODS

The work requires a variety of subjects having different health condition like healthy, diabetic, pre-diabetic and hypertensive. The participant who agreed to involve in the project is signed in consent form. The age range of participants varies from 22 upto 52 are involved in work. The younger participants are almost healthy, mid-aged subjects are in pre-diabetic state and some others are in diabetic state.

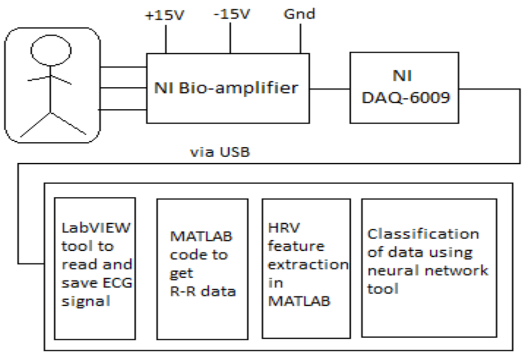


Figure 1: Assessment ANS Using HRV

Amplifier and Electrodes

In this work, for HRV feature extraction 3 lead ECG is used, that is acquired using clip-electrodes which are connected to left arm, right arm and to right leg of subject. The electrodes are connected to Bio-amplifier.

An amplifier is a device used to increase the gain of a signal normally, but when we come across biological signals like ECG, EMG, and EEG etc. are very weak in amplitude and gain. Hence ordinary amplifier cannot used to amplify biological signals, so we have employed the Bio-amplifier which can able to amplify weaker biological signal that can able to process by other electronic device. In this work we used NI Bio-amplifier, which has 3 lead ECG input with ±15V and a ground giving amplified ECG signal as an output.

DAQ-6009

The analog output from Bio-amplifier is connected to DAQ 6009. The DAQ work as analog to digital converter and also to creates an interface between computer and amplifier. This USB DAQ has eight analog input (AI) channels, two analog output (AO) channels, 12 digital input/output (DIO) channels, and a 32-bit counter with a Full-Speed USB interface. It has built in ADC, DAC, microcontroller, USB port, I/O ports.

ECG Data Acquisition and Recording

The DAQ-6009 is interfaced with PC by using Lab VIEW (LABoratory Virtual Instrument Engineering Workbench) software tool developed by National Instruments, used to read and record of variety of biological signal. Here it is used to read ECG data and also to record it. Lab VIEW provides a wide range of potions to record, process, analyze and to store the signals. The amplified signal from bio-amplifier is connected to DAQ which creates an interface with PC where we store and process the acquired ECG signal. The Lab VIEW provides a wide range signal processing options for removal of unwanted signals like power line interference, motion artifacts etc. DAQ interface is configured to acquire low voltage ECG signal and the input port is specified in configuration step. After configuring DAQ a set of analog filters are used to remove unwanted factors of signal like Low pass filter is used to remove the power line interference. The specifications of filters are:

LPF: Mode: IIR Filter, Topology: Butterworth, Order: 2, Cutoff: 50 Hz.

BPF: Mode: IIR Filter, Topology: Butterworth, Order: 2, Cutoff: 0.5 - 30 Hz.

BSP: Mode: IIR Filter, Topology: Butterworth, Order: 2, Cutoff: 42.3 – 82.5 Hz.

The processed signal is almost free form noise but it further pre-processed before analyzing it for further action of work. Finally data is stored in .txt format for make it possible to read in MATLAB for further processing action.

Inter Beat Interval Extraction

The stored ECG files which are in .txt format are read into MATLAB to extract IBI data. The time interval between two successive R-R peaks is known as Inter Beat Interval data [3]. Before this the data is pre-processed using analog and digital filtering techniques to remove noise and baseline shift.

Analog Filter Specifications

Type: Butterworth, Order = 1, Wp=0.075, High pass filter

Digital filters are used to remove the zero phase distortion form signal.

From the filtered output QRS complex to extract R-R peak for ANS assessment by threshold operator using MINPEAKHIGHT function.

HRV FEATURE EXTRACTION

Form the IBI data the heart rate variability features are extracted using developed MATLAB code. There are number of features can be found, but here we are used time domain, frequency domain, geometrical methods and nonlinear analysis for classification of subjects depending on their health conditions.

The features used for analysis are listed below:

Mean IBI

The interbeatinterval (IBI) is the time between one R wave (and heart beat) and the next, in milliseconds. IBI is highly variable within any given time period. The average value of IBI values over a wide time interval is called as mean IBI. Like a fingerprint, each individual's heart rate variability is unique. This "fingerprint" reflects all of the fluctuating neurological, immunological, and hormonal processes that occur in a human body. Normal value of IBI is 820 ms, i.e., 72 heart beats per minute.

Heart Rate

Heart rate is a non-stationary signal and provides a powerful interplay between the sympathetic and parasympathetic nervous systems. Heart rate is defined as "the number of heartbeats per unit of time, typically expressed as beats per minute (bpm)".

Standard Deviation of Heart Rate

Standard deviation (represented by the symbol sigma, σ) shows how much variation or dispersion exists from the average (mean), or expected value. A low standard deviation indicates that the data points tend to be very close to the mean; high standard deviation indicates that the data points are spread out over a large range of values. The SDNN can be defined as standard deviation of normal-normal (NN) values.

Sample Entropy

Entropy is a thermo-dynamical quantity that describes the amount of disorder in a system. The Spectral Entropy

shows the complexity of the input time series (RR-intervals) in the frequency domain. Large values of SpEn show high irregularity and smaller values of it indicate more regular time series. The Shannon's channel entropy is used to estimate the spectral entropy of the process. It is given by: Samp En= -∑Pf log (Pf)

In which Pf is the value of the probability density function (PDF) of the process at frequency f. Hence, the entropy can be considered as a measure of uncertainty about the event at frequency f.

Poincare Plot

The Poincare plot of RR intervals is one of the techniques used in heart rate variability (HRV) analysis. It is both a useful visual tool which is capable of summarizing an entire RR time series derived from an electrocardiogram in one picture, and a quantitative technique which gives information on the long- and short-term HRV [4].

The values of SD1 and SD2 are given by:

$$SD_1^2 = \frac{1}{n}\sum_{i=1}^{n}(d_i{}^1)^2$$

$$SD_2^2 = \frac{1}{n}\sum_{i=1}^{n}(d_i{}^2)^2$$

A Poincare plot of RR intervals is composed of points (RRi, RRi+1), that is each point in the plot corresponds to two consecutive RR intervals. The resulting cloud of points is usually characterized by its length (SD2) along the line of identity and its breadth across this line (SD1).

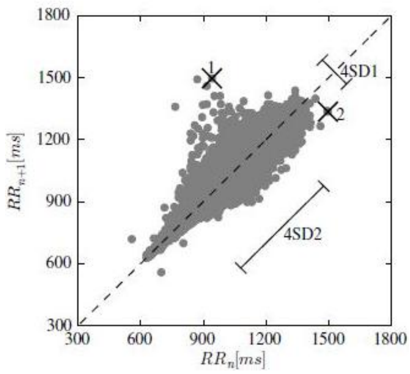


Figure 2: A Sample Poincare Plot of Healthy Person

CLASSIFICATION OF DATA

NeuroIntelligence is neural network software for experts. It is used to apply neural networks to solve real-world forecasting, classification and function approximation problems [11]. It is fast, intelligent and easy to use. NeuroIntelligence is full-packed with proven techniques for neural network design and optimization. It is designed to help you gain the maximum productivity in preprocessing data, find efficient network architecture, analyze performance and apply the network to new data.

Advantages

- Maximum productivity.

- Automatic data analysis and preprocessing.
- Auto searching of suitable network.
- Best training algorithms and techniques.
- Methodological approach

Table 1: Steps Involved in Neurointelligence Analysis

Step	How to
Load input dataset	Click Open on the main toolbar.
Select target column	Use Target drop-down list on the Analysis toolbar.
Design network	Click Architecture Search on the main toolbar (or manually select number of hidden layers and units in the Design window).
Train network	Click Train on the main toolbar.
Query network	Click Manual Query, Query Dataset or Load Query File on the main toolbar.

Algorithm for Assesment of ANS

Step 1*:* Collection of ECG data using LabVIEW signal express with appropriate basic filtering.

Step 2*:* Pre-processing of data to remove baseline wanderence. This involves analog filtring to remove unwanted frequency and digital filtering to remove zero phase shift.

Step 3*:* Detection of QRS complex to extract IBI data by taking threshould peak value.

Step 4: Feature extration of HRV using IBI data is done with help of MATLAB tool. This include time, frequency, nonlinear, and geometrical domain analysis.

Step 5: Data classification based on health condition of subject is done using neural networks method by taking different features HRV from previous step. Classification of data can also be done by observing geometrical analysis like poincare plot, which show a markable difference between healthy and unhealthy data.

RESULTS

DATA ACQUISITION

The ECG signals were derived from the LabVIEW instruments and Physio Bank Database. The sample size of data required for analysis is not specific. So, available numbers (62) of data are used for analysis purpose which includes healthy male, female, diabetics, pre-diabetics and hypertensive patients are taken for analysis with their permission.

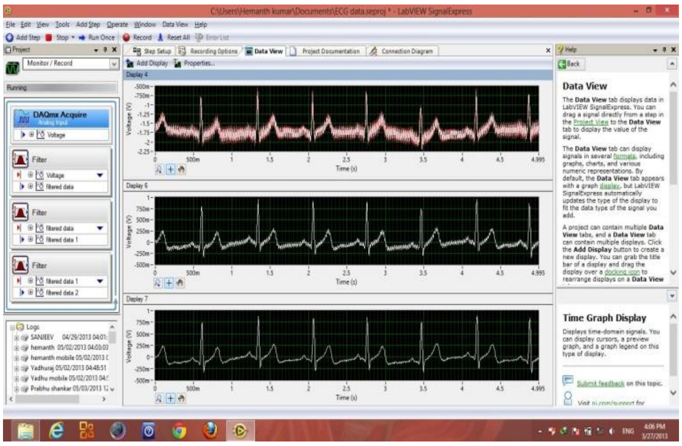
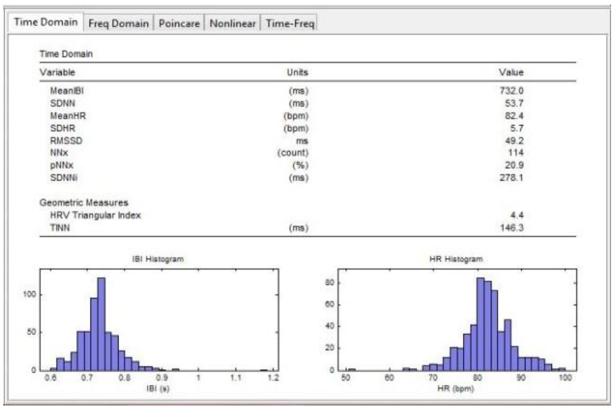


Figure 3: The Acquired Signal is Displayed on the Front Panel of Labview Environment

Front panel of LabVIEW software showing the ECG signal acquired using LabVIEW modules. Figure shows the file which is obtained after ECG data is acquired using LabVIEW. This file which is in the .lvm form has to be converted in to .dat form so that the file can be imported in to the MATLAB environment for RR-interval extraction.

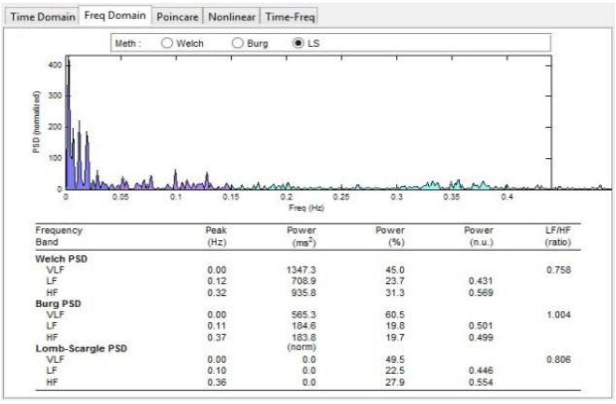
HRV Feature Extraction

The developed MATLAB code is to calculate the linear, non-linear and geometrical features taking IBI data as input. The obtained R-R data are copied into a text file and save it with a suffix '_rr.txt' to indicate it as R-R file for loading it to analysis.



Variable	Units	Value
Time Domain		
MeanIBI	(ms)	732.0
SDNN	(ms)	53.7
MeanHR	(bpm)	82.4
SDHR	(bpm)	5.7
RMSSD	ms	49.2
NNx	(count)	114
pNNx	(%)	20.9
SDNNi	(ms)	278.1
Geometric Measures		
HRV Triangular Index		4.4
TINN	(ms)	146.3

Figure 4: Time Domain Features of HRV



Frequency Band	Peak (Hz)	Power (ms^2)	Power (%)	Power (n.u.)	LF/HF (ratio)
Welch PSD					
VLF	0.00	1347.3	45.0		0.758
LF	0.12	708.9	23.7	0.431	
HF	0.32	935.8	31.3	0.569	
Burg PSD					
VLF	0.00	565.3	60.5		1.004
LF	0.11	184.6	19.8	0.501	
HF	0.37	183.8	19.7	0.499	
Lomb-Scargle PSD		(norm)			
VLF	0.00	0.0	49.5		0.806
LF	0.10	0.0	22.5	0.446	
HF	0.36	0.0	27.9	0.554	

Figure 5: Frequency Domain Features of HRV

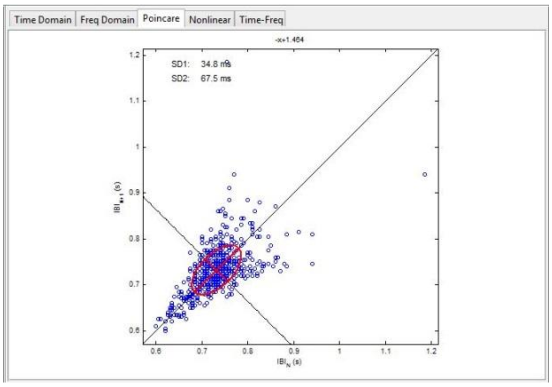


Figure 6: Poincare Plot of HRV

Tabulated Results

Table 2

SL No	Age	Gender	Mean IBI	HR	SDNN	NNx	SDNNi	TINN	Power	LF/HF	SampEn	Condition
Subject 1	22	F	836.2	72.3	56.8	110	316.7	154.7	670	1.279	1.971	Healthy
Subject 2	23	M	927	67.1	84.9	296	242	295.3	3813.9	0.526	2.294	Healthy
Subject 3	43	M	762.2	78.8	19.4	13	6.8	72.7	44.9	1.958	2.129	Prediabetic
Subject 4	53	M	707.5	84.8	8	0	213.4	3.4	2.1	9.213	1.1	Hypertension
Subject 5	22	F	735.9	82.6	89.7	183	280.9	182.8	3846.4	0.49	2.047	Healthy
Subject 6	32	F	873.7	68.9	68.9	131	332.5	181.6	1016.8	0.612	2.087	Healthy
Subject 7	22	F	724	83.9	60.9	15	413.7	208	575.5	1.281	1.725	Healthy
Subject 8	22	M	825.2	77.5	389.4	74	326.9	334.4	30888	0.9	0.398	Healthy
Subject 9	23	M	732	82.4	53.7	114	278.1	146.3	935.8	0.758	2.238	Healthy
Subject 10	22	F	755.4	80.1	70.9	778	378	329.4	1963.3	0.185	2.09	Healthy
Subject 11	45	M	718.9	83.8	43.3	456	217.5	161.7	164.3	0.816	3.288	Prediabetic
Subject 12	26	F	865.8	69.4	37.6	20	501.6	106.3	173.7	2.345		Healthy
Subject 13	32	F	688.1	87.5	43.9	6	218	110.2	566.1	1.286	1.938	Healthy
Subject 14	40	M	729.7	84.9	103.7	16	221.9	188.1	15394	1.572	0.659	Hypertension
Subject 15	35	M	653.8	92.4	58.6	167	165.3	72.5	1403.9	0.855	1.444	Healthy
Subject 16	23	M	846	73.2	76.2	228	246	292.5	2934.8	0.5	2.158	Healthy
Subject 17	22	M	721.6	85.3	91.1	49	228.6	196.4	5884.7	0.469	1.621	Healthy
Subject 18	24	M	896.5	71.1	143.8	711	226.9	520.6	11331	0.271	2.382	Healthy
Subject 19	24	M	809.4	74.8	59.7	76	331	232.8	729.5	1.457	1.935	Healthy
Subject 20	25	M	864.3	69.7	49.9	118	240.2	201.1	589.5	1.527	3.242	Healthy
Subject 21	45	M	860.5	73.3	63.7	25	273.1	146.9	462.4	0.955	1.486	Prediabetic
Subject 22	52	M	766.7	78.3	12.8	0	198.1	13.1	5.2	4.2	1.292	Diabetic
Subject 23	23	F	859.7	70.2	63.5	38	354.4	118.6	426.5	2.486	1.724	Healthy
Subject 24	22	M	689	87.4	87.4	8	281.5	111.6	151.8	4.481	2.636	Healthy
Subject 25	25	M	956	65.7	103.8	77	565.4	335.9	2544.9	0.416	1.887	Healthy
Subject 26	44	M	764.2	76.2	18.5	12.3	6.9	73.2	45.2	1.954	2.368	Prediabetic
Subject 27	46	M	765.2	76.3	17.2	13.4	6.6	72.4	42.7	1.938	2.567	Prediabetic
Subject 28	47	M	766.2	73.1	15.2	15.3	6.4	72.4	49.4	1.678	2.7893	Prediabetic
Subject 29	43	M	765.7	75.4	17.9	14.9	6.2	72.4	44.2	1.234	2.68	Prediabetic
Subject 30	47	M	763.2	79.4	16.3	12.8	5.9	76.4	44.2	1.598	2.472	Prediabetic
Subject 31	37	M	760.2	74.3	19.2	13.2	7.1	73.2	44.1	1.348	2.937	Prediabetic
Subject 32	49	M	769.2	76.2	17.3	14.8	7.2	72.4	48.4	1.376	2.57	Prediabetic
Subject 33	48	M	769.4	74.5	16.2	14.2	6.2	78.3	45.5	1.237	2.683	Prediabetic

hrvsnalysis

Ready

A snapshot of tabulated data's and results (total 62 subjects)

Symbolic entropy values are almost the same. Also we can see that Symbolic entropy is independent of the length of the data. Hence, No significant information can be obtained to differentiate between thyroid and healthy subjects

Symbolic Entropy values of Different types of subjects

Table 3

Sl. No	Name of the Sample	Symbolic Entropy (Avg)
1.	Healthy	1.989
2.	Prediabetic	1.486
3.	Diabetic	1.292
4.	Hypertension	2.129

Graphical Representations Poincare Plot

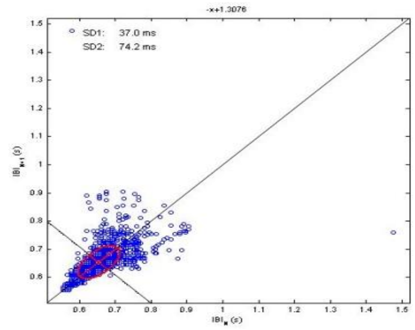


Figure 7: Poincare Plot of Healthy Subject

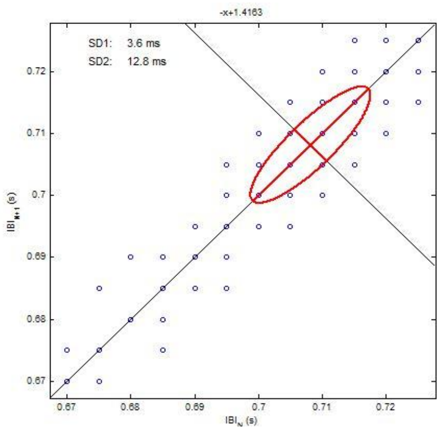


Figure 8: Poincare Plot of Diseased (Diabetic) Patient

So, by observing above figures we can conclude that the Poincare plot is an excellent marker which helps to distinguish the subject's health status as healthy or diseased.

CLASSIFICATION USING NEURAL NETWORK

For analysis of HRV data using this neural network tool is done to classify data as healthy, diabetic, and pre-diabetic or hypertensive subjects. The data base of acquired signal is done in an MS-Office Excel sheet with distinct features. Now, data is processed and trained to select appropriate network. After training the network we can give input HRV data's to classify the given data to check the condition of given subject. The below snapshot shows an example of neural network tool for a given set of input data.

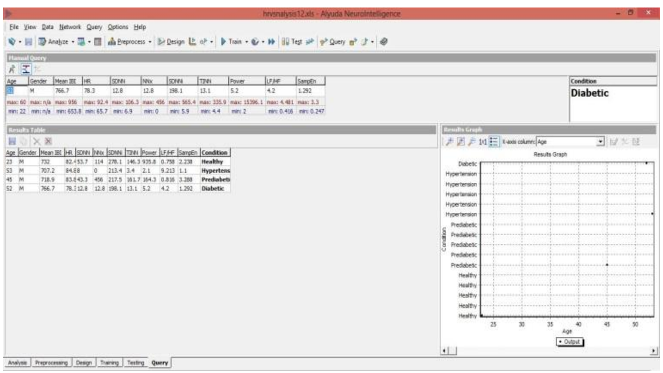


Figure 9: Snapshot of Trained Result for Given Input Data

A snapshot of trained result for given input dataAlyuda NeuroIntelligence tool is used to analyze and classify data to its respective health condition of subject. This work includes a wide range of data collection of 62 subjects of different health conditions; the acquired ECG data using LabVIEW tools are processed in order to calculate inter beat intervals of ECG data. This IBI data is used to extract the HRV parameters, which are imported in NeuroIntelligence tool to classify it as healthy, hypertensive, pre-diabetic or diabetic patient using appropriate neural network[10]. The above snap shot from NeuroIntelligence shows some examples of different health conditions.

CONCLUSIONS

ECG data are extracted using LabVIEW signal express tool efficiently with the help of bio-amplifier, DAQ-6009 and clip electrode which shows all significant features of ECG. The data acquired is processed to calculate R-R interval. The obtained R-R interval is used to extract HRV features to specify the health status of subject using NeuroIntelligence tool. The project work focused on analyzing 4 different states of an individual such as healthy, pre-diabetic, diabetic or hypertensive as according to its time, frequency and non-linear values. The Poincare plot shows mark able difference between health and unhealthy subjects by its distribution pattern. The work confirms that there will be gradual decrease in HRV as age increases. Diabetic patients are also has decrease in HRV comparatively higher than the normal individuals, and also DM patients shows lower values in SDNN, SampEn, LF/HF value and HF power. Hypertensive subjects has higher values of sympatho-vagal balance than normal subjects, this condition even present in the diabetic patients but with comparatively lesser values than hypertension patients.

DISCUSSIONS

The non-linear analysis like different entropy methods and Detrended Fluctuation Analysis (DFA) are very recent techniques. Hence a lot of research needs to be done on the properties so that we can come up with still simpler methods for ECG signal Analysis. The combination of different analyzing methods in single package to acquire and analyze can be made with added easy user interfaces for faster and accurate analysis of health status of an individual. Comparative analysis can be done with using other available tool to analyze HRV to get more accurate and guarantee results.

REFERENCES

1. U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, Choo Min Lim, Jasjit S. Suri “Heart rate variability: a review”, Med Bio Eng Comput (2006) 44:1031–1051.
2. Nirmal D. Thakur, Manoj S. Sankhe, Dr. K. D. Desai, “Implementation of HRV system for understanding behavior of autonomous nervous sytem”, International Journal of Electronics and Computer Science Engineering, ISSN 2277-1956, 2007.
3. H. Naka, T. Tohara, K. Inoue “Influence of Undetected ECG R waves on the Heart Rate Variability Analysis” SICE Annual Conference August 20-22, 2008, The University Electro-Communications, Japan, pp 3189-3193.
4. J Piskorski and P Guzik, “Geometry of the Poincar´e plot of RR intervals and its asymmetry in healthy adults” Institute of Physics, University of Zielona Gora, Prof. Szafrana 4a, 65-516 Zielona Gora, Poland Department of Cardiology-Intensive Therapy, University of Medical Sciences in Poznan, Przybyszewskiego
5. HosseinFakhrzadeh, et al, “Cardiac Autonomic Neuropathy Measured by Heart Rate Variability and Markers of Subclinical Atherosclerosis in Early Type 2 Diabetes”, International Scholarly Research Network ISRN

Endocrinology Volume 2012, Article ID 168264.

6. Mohamed Faisal Lutfi, Mohamed YosifSukkar, "Effect of blood pressure on heart rate variability", Khartoum Medical Journal, Vol. 04, No. 01, pp. 548 – 553, 2011
7. Stuart Crozier, ans Stephen Wilson "A new heart rate variability analysis methods by means of quantifying the variation of non-linear of non-linear dynamic patterns Hang Ding, IEEE transactions on Biomedical engineering, Vol. 54, NO.9, pp 190-197, 2007.
8. Blair P. Grubb, M.D., Barry Karas, M.D., "Clinical Disorders of the Autonomic Nervous System Associated With Orthostatic Intolerance: An Overview of Classification, Clinical Evaluation and Management", Cardiology, The Medical College of Ohio, Ruppert Health Center.
9. Bigger JT Jr, Fleiss JL, Rolnitzky LM, Steinman RC, Schneider WJ. "Time course of recovery of heart period variability after myocardial infarction". J Am CollCardiol 1991; 18: 1643–9.
10. Pagani M, Malfatto G, Pierini S et al. Spectral analysis of heart rate variability in the assessment of autonomic diabetic neuropathy. J AutonNerv System 1988; 23: 143–53.
11. Kienzle MG, Ferguson DW, Birkett CL, Myers GA, Berg WJ, Mariano DJ. Clinical hemodynamic and sympathetic neural correlates of heart rate variability in congestive heart failure. Am J Cardiol 1992; 69: 482–5.